DENOISING EMG AND EEG FOR MONITORING SMALL ANIMAL MODELS DURING NMR EXPERIMENTS

O. FOKAPU[1], H. CHAHBOUNE[2], M. ARMENEAN[2], P.DESGOUTTE[2], R.CESPUGLIO[3], A.BRIGUET[2]
[1]Laboratoire GBM, UMR CNRS 6600, Université de Technologie, 60203 Compiègne France.
[2]Laboratoire de RMN, UMR CNRS 5012, Université Claude Bernard Lyon 1, 69616 Villeurbanne France.
[3]INSERM U 480, Neurobiologie, Université Claude Bernard Lyon 1, 69373, France

Abstract - The present growing field of molecular imaging, including multimodality microimaging techniques and spectroscopic approaches, is mainly based on small animal studies. Monitoring such models requires an efficient treatment and use of electrophysiological signals which may be spoiled by environmental effects especially when working with nuclear magnetic resonance (NMR) since radiofrequency (RF) pulses and magnetic field gradient commutations may create spurious supplementary signals. In this work, a method is given for EEG and EMG denoising of signals acquired during phosphorous magnetic resonance (MR) brain spectroscopy data acquisition on a rat model developed for sleep/awake studies. The proposed approach is based on wavelet decomposition and the key method is to turn into profit the shape variations of EMG during the time course of sleep/awake cycles. Statistical properties of the noise are studied using EMG recorded during paradoxical sleep as noise model. A specific estimation of noise level using EMG recorded during slow sleep leads to an optimal wavelet coefficients thresholding. This approach is well suited to improve signal to noise ratio of EEG and EMG and to preserve small amplitude electrophysiological signals.

Keywords : EEG, EMG, wavelet transform, noise, wavelet shrinkage, NMR, sleep/awake states.

I. INTRODUCTION

Simultaneous acquisition of several physiological signals is currently employed for NMR investigation of living beings. The extracted parameters permit one to correlate the observed variations of NMR data with functional states for diagnostic evaluation or physiological studies. NMR systems represent a really hard situation due to a very particular electromagnetic environment which may obscure small amplitude signals [1]. For small animals, the electrophysiological signals may be shrouded by some NMR artefacts, consequently it is important to employ an efficient filter before these signals are used as a monitoring reference.

Here, the considered NMR experiment is devoted to brain phosphorous metabolites detection during sleep and awake states on the rat model. NMR spectroscopy [2] may represent an efficient way to observe the time course of metabolites concentrations in tissues. Nevertheless this method presents a rather weak sensitivity, especially with isotopes such as ^{31}P in metabolites at low concentration, so it requires usually averaging of data. In this particular application, one must associate properly collected NMR data with their corresponding sleep state (awake, paradoxical sleep, normal sleep). In the present work, EEG and EMG signals are simultaneously recorded with NMR spectroscopy data collection on a rat brain model observed during sleep and awake states. Considering the low amplitude levels and the possible cross talk with NMR, it appears that conventional signal processing approaches are not well suited because the sleep/awake states identification is possible with clean electrophysiological signals only. Here a method based on wavelet decomposition is proposed and tested in order to remove noise from EEG and EMG. Starting from the specific properties of EMG, an algorithm was developed and then applied to the EEG analysis as it will be indicated in the first part of the presentation in which the denoising technique using wavelet decomposition based applied to EEG and EMG is given. Then a specific strategy will be developed for sleep state identification for an efficient use in NMR experimental conditions.

II. THEORETICAL CONSIDERATIONS

1. Electrophysiological signals and Magnetic Resonance (MR) Environment.

During MR experiments the signal S(t) is acquired by the EEG or EMG sensor, it does not contain the electrophysiological information $S_{el}(t)$ only, but it involves also some “interference” components due to MR environment. According to Felblinger [3], the signal S(t) can be modelled by the following equation :

$$S(t) = S_{el}(t) + S_{flow}(t) + S_{move}(t) + S_{MR}(t) + S_{rf}(t) \quad (1)$$

In equation (1) $S_{el}(t)$ represents the signal to be analysed. $S_{flow}(t)$ has its origin in the flow of electrically charged particles through the magnetic field. $S_{move}(t)$, $S_{MR}(t)$, $S_{rf}(t)$ are induced signals due to electrical and magnetic sources present in the environment : $S_{move}(t)$ is induced by patient-related sensor motions, $S_{rf}(t)$ is created by radiofrequency pulses application and $S_{MR}(t)$ is due to the temporal variations of the magnetic field gradients. In NMR spectroscopy situation, equation (1) reduces to :

$$S(t) = S_{el}(t) + S_{flow}(t) + S_{move}(t) + S_{rf}(t) \quad (2)$$

2. Electrophysiological signals and sleep states relationship.

From electrophysiology, the awake state (AS) is characterized by a fast and slight brain cortical activity with low amplitude. Simultaneously a strong muscular activity dealing to large amplitude signals may be observed. Normal sleep, designed here by NS, provides slow brain cortical waves with a weak muscular activity in parallel. During paradoxical sleep (PS) the brain cortical activity is quite identical to the AS one but the muscular activity disappears

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Denoising EMG and EEG for Monitoring Small Animal Models During NMR Experiments	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) Laboratorie GBM UMR CNRS 6600, Universite de Technologie 60203 Compiegne France	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited	
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom.	
Abstract	
Subject Terms	
Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU
Number of Pages 4	

leading to a very poorly informative EMG signal. It may be observed that in any case, spectral components of EEG are between 1 Hz and 35 Hz and that EMG spectral components are spread on the 100 to 500 Hz range approximately. Since the corresponding signals are polluted, as mentioned above, several processing techniques may be employed to provide useful informations from their records. To restrict the spectral bandwidth of amplifiers is not a solution since some noise can overcome the low frequency components of EEG and EMG. Band-pass filtering is no longer efficient since spectral overlap of noise and desired components of EMG and EEG occurs. In such case, the wavelet decomposition has proven to be particularly suited.

3. Wavelet shrinkage for signal denoising

It has been demonstrated that the wavelet transform method achieves a maximum number of vanishing moments, therefore a substantial degree of separation between signals and noise can be obtained in the wavelet domain.

(a).White noise: In the case of an additive white and assumed Gaussian noise, the problem consists to estimate the real signal x(t) from its noisy realisation designed as : y(t) = x(t) + b(t) (3)

where b(t) is a zero-mean Gaussian noise with a variance σ^2. If the wavelet basis is orthogonal, the white noise stands as a white one with the same magnitude and it is completely uncorrelated over all wavelet scales. Consequently, equation (3) is equivalent to :

Wy = Wx + Wb (4)

where Wy, Wx and Wb are the wavelet transforms of y(t), x(t) and b(t) respectively. To obtain an estimate of the noise-free signal, one just has to remove the noise contribution from Wx. In this aim, a wavelet shrinkage technique was proposed by Donoho [4] and it consists of shrinking each wavelet coefficient using one of the following functions :

- « hard- thresholding » defined as

$$H_{j,k} = \begin{cases} 1 & if \quad \left|Wy_{j,k}\right| > T \\ 0 & otherwise \end{cases} \qquad (5)$$

- « soft-thresholding » defined as

$$H_{j,k} = \begin{cases} \frac{sgn\left(Wy_{j,k}\right)}{Wy_{j,k}}\left[\left|Wy_{j,k}\right| - T\right] & if \quad \left|Wy_{j,k}\right| > T \\ 0 & otherwise \end{cases} \qquad (6)$$

T denotes a fixed threshold which depends on the noise variance. Different approaches have been proposed for the estimation of *T*. $T = \sigma\sqrt{2\log(N)}$ termed universal threshold was proposed firstly by Donoho [4]. N represents here the number of data samples. The noise dispersion σ is estimated on the first scale which mainly contains noise coefficients.

(b) Correlated noise : The case of a correlated noise has been studied by Johnstone and Silverman [5]. They showed that the log-variance of the noise decreases roughly linearly with the scale. On each scale, the noise coefficients follow approximately a Gaussian distribution. From this statements, Johnstone and Silverman proposed a level-dependent thresholding T_i for the wavelet coefficients shrinkage : $T_i = \sigma_i\sqrt{2\log(N_i)}$, where σ_i is the noise standard deviation at scale i.

III. METHOD

Successive steps of the denoising method were performed using the EMG signal as basis of the study, and then applied to the EEG one. The method turns into profit the shape variations of EMG during the time course of sleep/awake cycles**.** It included the following two main steps : (i) noise modelling and statistical analysis and (ii) wavelet coefficients thresholding.

1. Noise modelling and statistical analysis

In order to investigate more precisely the nature of the noise corrupting EEG and EMG, we searched for a model approaching the noise generated by the MR environment. It is known that, during paradoxical sleep, there is a total absence of muscular activity. Therefore, the signal captured during this state by the EMG amplifier does not contain any useful information. This leads to assume that noise can be modelled by a segment of EMG recorded during the PS state. Considering the statistical behaviour of this model and after an orthogonal wavelet transform of a PS segment over 4 scales with Daubechies 4 , it was possible to represent the histogram of wavelet coefficients. It was noticed that, on each scale, the noise coefficients followed approximately a Gaussian distribution. Consequently the white noise hypothesis could not satisfy this situation.

2. Wavelet coefficients thresholding

EEG and EMG recorded from small animals are very weak, the challenge is to attenuate the noise while preserving the low amplitude signals. Instead of using a level-dependent thresholding proposed by Johnstone and Silverman [5], an udapted version was used here. In this adaptation, the noise reduction was achieved by wavelet coefficients shrinkage, using an optimal and experimental threshold T_i having the following expression :

$$T_i = \sigma_i\sqrt{\frac{2\left(\log(N_i)\right)}{N_i}} \qquad (7)$$

where N_i is the coefficients number and σ_i the noise level at scale i.

To avoid some loosing of the signal of interest during the wavelet shrinkage, an other manner for estimating the noise level was considered. On each detail signal d_i, σ_i was estimated. The optimisation of T_i was based on a specific estimation of the noise standard deviation using a segment of EMG signal recorded during normal sleep (NSEMG). The principle is described below.

(a). Use of NSEMG segment for noise estimation

On an EMG intramuscular signal, one may distinguish active segments from no active ones. While processing

EMG signals for some specific applications, the EMG segments which do not contain any spike potentials are treated as noise segments and they are used to estimate the noise standard deviation [6],[7]. In experiments, it was observed that noise increases with muscular activity intensity. The interference was more important during awake phase than the NS state or than during PS. The spike potentials and artefacts are superimposed during this phase, making the noise detection segments difficult. Therefore, estimation of the noise level on NSEMG signal could be performed : In Figure 1 a raw of NSEMG is given with details signals obtained after the wavelet decomposition. Spike potentials appear clearly on details. The noise standard deviation of each detail signal could be estimated after extraction of noise segments of the corresponding detail.

(b) Extraction of noise segments

A simple and robust algorithm was established for noise segment extraction which included the following steps : computation of the squares of first and second derivatives of a given signal, specific smoothing (zero-phase filter) of each square derivative, application of a numerical Schmitt trigger with relative low thresholds on the sum of smoothed squares derivatives. In order to simplify computation and implementation, we build a unique function noted DSF to combine derivation and smoothing operations :

$$DSF = (dr1 * sm5)^2 + (dr2 * sm5)^2 \qquad (8)$$

where $y_1 = dr1 * sm5$, is the smoothed first derivative,

$y_1 = 1/32[(x_{n+3} - x_{n-3}) + 4(x_{n+2} - x_{n-2}) + 5(x_{n+1} - x_{n-1})]$;

where $y_2 = dr2 * sm5$, is the smoothed second derivative,

$y_2(n) = 1/16[x_{n+3} + x_{n-3} + 2(x_{n+2} - x_{n-2}) - (x_{n+1} - x_{n-1}) - 4x_n]$ and where x(n) is a sequence of the input signal.

DSF is a non linear band-pass filter function allowing the best spike potentials isolation and leading to a valuable noise segments extraction.

The procedure was applied to each detail obtained after the orthogonal decomposition of a NSEMG segment. An illustration is given in Figure 2. Thus, the noise level σ_i for different scales could be estimated.

3. Application

(a). Signals pre-processing

EEG and EMG signals were simultaneously recorded and analogue band-pass filtered at 1-500Hz. For the best representation of the information contained in each signal, EEG and EMG were pre-processed before denoising. EEG was numerically filtered over 1-40 Hz. In order to take into account more precisely the interference corrupting the EEG, the segment of NSEMG used to estimate the noise level for EEG denoising, was filtered in the same manner. For EMG signals, the band-pass filter was set at 100-500Hz.

(b).Denoising

The procedure was implemented according the denoising classical scheme including wavelet signal decomposition, wavelet coefficients shrinkage and reconstruction of the signals by inverse wavelet transform. In this study, the wavelet selected for the transformation is the Daubechies wavelet with four vanishing moments. The reason of this choice is a good trade off between noise reduction and over smoothing. The thresholds T_i for wavelet coefficients shrinkage were calculated using the experimental optimal formula where σ_i are estimated using the procedure previously described.

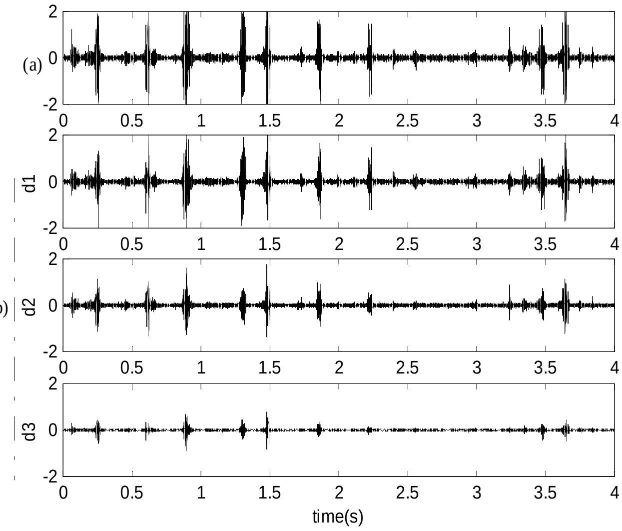

Fig.1 Wavelet decomposition of a NSEMG segment. (a) raw of NSEMG signal. (b) detail components (d_1,d_2,d_3) obtained on 3 scales using Daubechies (D_4).

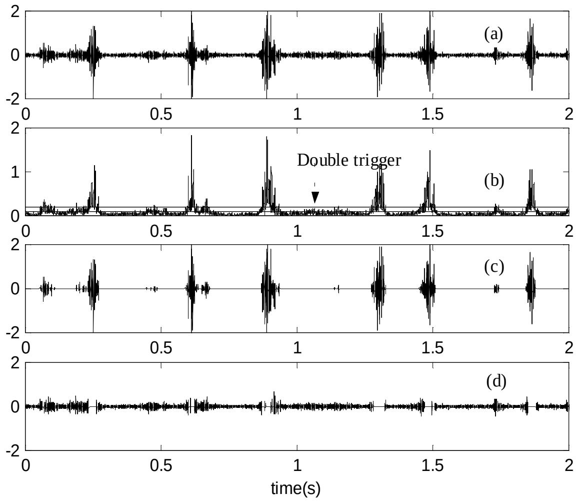

Fig. 2 : Illustration of noise segment extraction procedure. (a) detail component d_1. (b) sum of the squares of first and second derivatives, (c) spike potential segments, (d) noise segments.

IV. RESULTS

Data acquisition were experimentally performed on non anaesthetized rats. The three kinds of data (NMR, EEG and EMG) were simultaneously collected for rather long periods, until several hours, of spectroscopy measurements. Bipolar electrode was screwed in the rat nape for intramuscular EMG detection. EEG was collected on the top of the cerebral cortex through two small electrodes. EEG and EMG signals were analogue band-pass filtered at 1-500 Hz, and sampled at 2 kHz. NMR signals were provided using a surface coil fixed on the rat skull and related to a SMIS console. A 2 teslas Oxford magnet provided the magnetic static field (phosphorous resonance frequency 34 MHz).

The noise standard deviation was estimated from 40 seconds long NSEMG segments. The algorithm was designed using Daubechies wavelets D_4. EMG and EEG signals were decomposed on 5 scales. Soft-thresholding function was used for wavelet coefficients shrinkage. In all situations EEG and EMG examination showed a level noise significantly greater than in the magnetic field free awake state. In Figure 3 are displayed the results obtained with this technique applied to EMG and EEG and corresponding to the awake period. One may notice the relatively high noise level corresponding to an intense muscular activity and the performance of the denoising algorithm.

V. DISCUSSION AND CONCLUSION

The efficiency of the proposed method is mainly based on the *a priori* knowledge of the noise properties and also on the thresholding optimisation of the wavelet coefficients. Simulation of NMR artefacts permits one to evaluate efficiently the statistical behaviour of the corresponding noise. The wavelet coefficients histogram leads to conclude that spoiling through NMR noise cannot be considered as a white and gaussian noise superimposition, certainly because of the particularities of sequence timing and coherent radiofrequency excitations which are not randomly performed. This was observed on segment corresponding to paradoxical sleep periods. This observation did not take into account motion artefacts due to displacements in the static field that may be more clearly observed during the awake state.

Thresholding optimization was achieved when taking into account of the local noise level in order to get efficiently small amplitude signals. Consequently the proposed method permitted one a real cleaning of the desired signal. Then data for sleep phase identifications [8] were correctly determined and data averaging was no longer an impediment for metabolism variations studies during the sleep/awake cycle.

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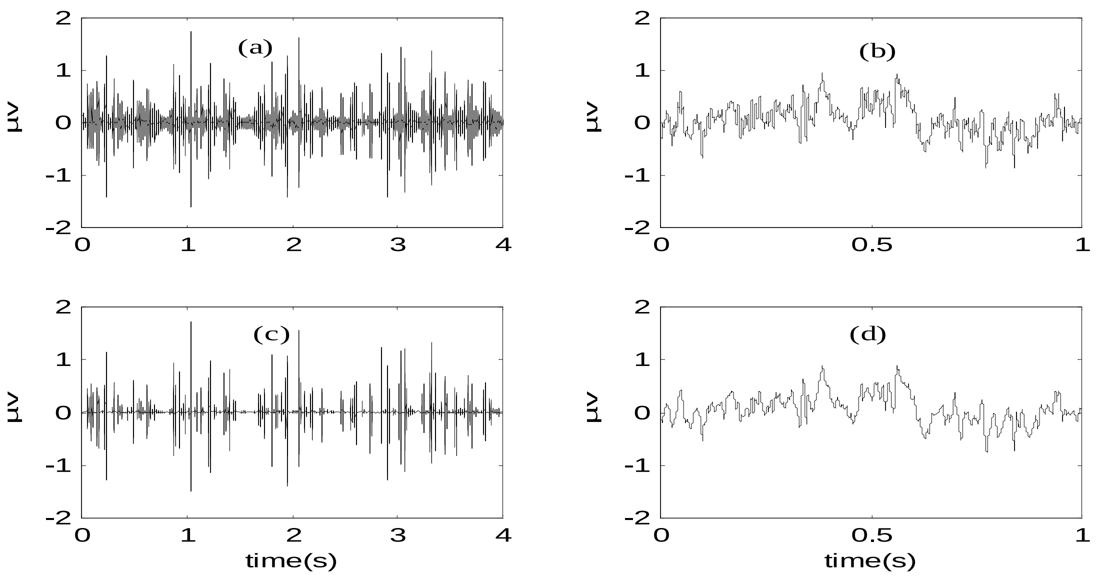

Fig. 3 Results of denoising method. The top rows represent the original awake states signals, (a) EMG, (b) EEG. The bottom rows represent their denoised versions, (c) noise-free EMG, (d) noise-free EEG.